DIAGNOSTICS OF THE TEMPERATURE CONDITION OF CAST IRON MELTING IN INDUCTION FURNACES BY THE CONTENT OF SiO_2 AND CaO IN SLAG

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ABSTRACT

The object of the research: temperature conditions for melting cast iron in induction crucible furnaces for machine-building castings.
Investigated problem: incorrect selection of temperature conditions for melting cast iron in induction crucible furnaces with acid lining or deviation from the rational temperature conditions cause the risk of chemical wear of the lining. It can be caused by the interaction of the melt and slag with the lining. If the possibilities of continuous temperature control are limited and, for this reason, the possibilities of rational control of the melting process are limited, then the problem of assessing the state of the process and the risk of lining wear arises.
The main scientific results: a mathematical description of the diagnostic rule for assessing the temperature conditions for melting cast iron in induction furnaces was obtained. It is a linear discriminant function of two variables, the value of which is compared with a certain threshold. Based on this comparison, it is possible to assess the temperature conditions of the process.
The area of practical use of the results of the study: the obtained results can be used in foundries of industrial enterprises equipped with induction crucible furnaces, in which castings from cast iron are made.
Innovative technological product: a diagnostic rule that allows for an indirect assessment of the melting temperature regime based on the SiO_2 and CaO content in the slag. This diagnostic rule can be part of a decision support system in the process of induction melting control or integrated with the melting control system.
The scope of the innovative technological product: technological processes of induction melting of cast iron at the level of an element of the system or the melting control process.

1. Introduction

1. 1. The object of research

The temperature regime of melting cast iron in induction crucible furnaces for machine-building castings.

1. 2. Problem description

The correct temperature regime of melting cast iron in induction furnaces is one of the main factors in obtaining a high-quality alloy. It is the temperature that affects the physicochemical processes occurring in the melt. The correct choice of temperature conditions forms the final chemical composition of the alloy, which must meet the requirements of standards or technical conditions for a given industrial production. However, not only the formation of the chemical composition of the alloy is the output characteristic of the induction melting process, formed mainly by the temperature of the alloy. It is very important to take into account the physicochemical interactions in the entire "melt - lining - slag" system. If these interactions are not taken into account, then situations of lining wear and melt breakthrough may occur. The risks of such situations are directly related to the correct choice and control of the temperature regime. Thus, when switching from a low-temperature mode T=1200–1300 °C to a high-temperature mode T=1400–1500 °C, a reaction of interaction between silica of the acidic furnace lining and the melt begins to develop:

$$2[\mathrm{C}]+(\mathrm{SiO_2}) \rightleftarrows [\mathrm{Si}]+2\{\mathrm{CO}\}, \qquad (1)$$

where [C], [Si] – the carbon and silicon content in the melt, %, (SiO_2) – the silica content in the lining, {CO} – the carbon monoxide content in the gas phase.

The development of reaction (1) leads to chemical wear of the lining.

However, this process is not the only one that is undesirable. Since the peculiarity of the induction process is melting with a liquid metal residue, which can be, based on practical recommendations, 25–50 %, during the melting process the position of the melt level along the furnace height changes from time to time. If the content of iron oxides (FeO) in the slag is high, then the complex compounds of the $FeO{\cdot}mSiO_2{\cdot}MnO$ type, which have a low melting point and pass all the time upward along the height of the lining, dissolve the silica included in the lining. The result of this is wear of the lining. On the other hand, the requirements for the chemical composition of the alloy and the dependence of induction melting on the quality of the charge determine the need to conduct melting in a high-temperature mode. Therefore, it is very important to control the process in such a way as to rationally ensure the temperature mode required for these conditions. If there is no possibility of continuous high-quality temperature control during the melting process, it is necessary to have high-quality diagnostic capabilities that allow indirectly assessing the process temperature. The absence of such capabilities creates a problem for the effective control of induction melting according to the criterion of ensuring the quality of the alloy and increasing the service life of the lining.

1. 3. Suggested solution to the problem

Melting control involves conducting the process in such a way that the chemical composition of the alloy must correspond to the specified one, while the control task is not simple due to many physicochemical transformations in the melt, determined by the composition of the charge and the melting conditions, including temperature. The results of studies of carbon conversion processes in induction melting processes, obtained by thermogravimetric analysis, make it possible to obtain kinetic equations describing heterogeneous carbon oxidation reactions in a carbon dioxide environment, which can be used to control melting [1, 2]. However, it is very important to take into account that the melting process involves periodically dispensing the finished melt from the furnace, i.e. the parameters of the kinetic equations require clarification. This is due to the fact that the mass of the melt and its chemical composition change from time to time, since the melt is discharged from the furnace at certain intervals to fill the molds. In this case, it is necessary to use an adaptive approach to obtaining kinetic equations [3]. This approach allows tracking the parameters of the kinetic equations for a reasonable choice of melting modes, primarily temperature ones. This is due to the fact that temperature affects the rate constants of processes. Deviations in temperature conditions can lead to obtaining an alloy that does not meet the requirements for chemical composition. The complexity of the practical application of kinetic equations is that continuous control of the temperature and composition of the alloy during the melting process is necessary, that is, the use of technical means of control, and with the receipt of results with a time shift. Manufacturers of modern induction furnaces, whose products are presented, for example, in [4–6], are trying to solve the problem of temperature control by means of automation. There is also a possibility of searching for optimal melting control according to the criterion of speed of response in ensuring a given temperature regime, using the Pontryagin maximum principle [7]. Its implementation, of course, requires continuous monitoring of the melting parameters. However, one should take into account the reliability of such elements of melting control systems operating in aggressive environments. Therefore, alternative solutions to temperature control issues should assume the possibility of indirect assessment. This approach is used in [8, 9], where it is proposed to use the slag composition as diagnostic parameters for indirect assessment of the temperature regime. This proposal can be considered justified, since slag is formed as a result of physical and chemical processes that depend on temperature. However, the disadvantages of these studies are the option of choosing diagnostic parameters – SiO_2 and $FeO+Fe_2O_3$ or SiO_2 and the distribution coefficient $K_p = \dfrac{\mathrm{SiO_2}}{\mathrm{FeO+MnO}}$. Therefore, further search for the most significant diagnostic parameters is necessary. In case of detection of such parameters, it is possible not only to more accurately diagnose the temperature regime and identify deviations from the specified regime, but also to identify the stage of the technological process responsible for the formation of functional failures [10–13]. The latter are recorded based on the fact that specific quality criteria or melting modes fall outside the established tolerance fields.

Research objective: to build a diagnostic principle for assessing the temperature regime of cast iron melting in an induction crucible furnace based on slag analysis, selecting the most significant slag components as diagnostic parameters.

2. Materials and Methods

The study was based on the concept proposed in [8], which states that the slag composition can be used to determine deviations of melting temperature regimes from normal ones. For this purpose, a classification rule was constructed that allows one to determine whether the melting was carried out in a low-temperature regime or in a high-temperature regime based on data on the content of determining components in the slag. SiO_2 (designation x_1) and CaO (designation x_2) were chosen as such components as the main components determining the acidity of the slag. To construct the classification rule, the following procedure was performed:

1. Scaling and normalization

2. Calculation of statistical characteristics for classes: class 1 – low-temperature melting mode, class 2 – high-temperature melting mode

3. Construction of the discriminant function

The classification rule has a general form:

$$f \geq f_0 \rightarrow x^{(j)} \in class\ 2,$$

$$f < f_0 \rightarrow x^{(j)} \in class\ 1. \qquad (2)$$

where f – the value of the discriminant function, calculated by formula (2), f_0 – the threshold value, calculated by formula (3), $x^{(j)}$ – the matrix of factors;

$$f(\mathbf{X}) = \mathbf{X}^{\mathbf{T}}\mathbf{C}^{\mathbf{-1}}(\mathbf{m}_1 - \mathbf{m}_2), \qquad (2)$$

$$f_0 = 0.5(\mathbf{m}_1 + \mathbf{m}_2)^{\mathbf{T}}\mathbf{C}^{\mathbf{-1}}(\mathbf{X})(\mathbf{m}_1 - \mathbf{m}_2) - \ln\frac{P(1)}{P(2)}. \qquad (3)$$

The following notations are used in formulas (2), (3): $\mathbf{m}_1$, $\mathbf{m}_2$ – the mathematical expectations of classes 1 and 2, respectively, calculated by formulas (4), (5):

$$\mathbf{m}_1 = N_1^{-1}\begin{pmatrix}\sum_{j=1}^{N_1} x_{1j} \\ \sum_{j=1}^{N_1} x_{2j}\end{pmatrix}, \qquad (4)$$

$$\mathbf{m}_2 = N_2^{-1}\begin{pmatrix}\sum_{j=1}^{N_2} x_{1j} \\ \sum_{j=1}^{N_2} x_{2j}\end{pmatrix},, \qquad (5)$$

C – the dispersion matrix, calculated by the formula:

$$\mathbf{C} = \frac{1}{N_i}\sum_{j=1}^{N_i}\mathbf{X}_{ij}\mathbf{X}_{ij}^{\mathbf{T}} - \mathbf{m}_i\mathbf{m}_i^{\mathbf{T}},\ \ i = \begin{cases}1 & for\ class\,1,\\ 2 & for\ class\,2,\end{cases} \qquad (6)$$

N_1, N_2 – the number of objects in classes 1 and 2, respectively,

$P(1)$, $P(2)$ – the probability of classes 1 and 2, respectively, were taken to be equal.

The rule was constructed for normalized values of factors, the standardization was carried out according to the formula:

$$x_{kj}^{norm} = \frac{2x_{kj} - \left(x_{k\max} + x_{k\min}\right)}{x_{k\max} - x_{k\min}},$$

$$k = 1,2, \quad j = 1,2,..., N_i,$$

$$x_{k\max} = \max_j x_{kj}, \quad x_{i\min} = \min_j x_{kj}, \tag{7}$$

where $x_{k\max}$, $x_{k\min}$ – the maximum and minimum values of factors (SiO_2 and CaO content in slag, %), respectively, for the generalized sample for low-temperature and high-temperature modes.

3. Results

Table 1 shows a truncated data sample obtained from [8] for constructing a classifying rule.

From **Table 1** it is evident that $x_{1\max}$=76.18 %, $x_{1\min}$=39.32 % $x_{2\max}$=4.11 %, $x_{2\min}$=2.08 %. Therefore, the average values are $m(x_1)$=57.75 %, $m(x_2)$=3.095 %, and the variation intervals I_1=18.43 %, I_1=1.015 %, respectively.

Table 2 presents the results of factor normalization, and **Table 3** presents the results of calculating the sample statistical functions – the mathematical expectation $M(X_i)$ and the variance $S^2(X_i)$ for the normalized values of the factors, where X_i – the component content in the slag, %

Table 1

Data sample for constructing a classifying rule

Sample No.	Slag composition, %			
	Low-temperature mode		High-temperature mode	
	SiO_2	CaO	SiO_2	CaO
1	39.32	2.08	56.62	3.11
2	44.55	2.13	65.38	3.14
3	47.16	2.52	76.18	3.18
4	50.17	2.76	70.85	4.11
5	53.22	3.18	69.95	3.59

Table 2

Data sample for constructing a classifying rule

Sample No.	Normalized values of factors			
	Low-temperature mode		High-temperature mode	
	SiO_2	CaO	SiO_2	CaO
1	–1	–1	–0.061313	0.014778
2	–0.716224	–0.950739	0.413999	0.044335
3	–0.574607	–0.566502	1	0.083744
4	–0.411286	–0.330049	0.710798	1
5	–0.245795	0.083744	0.661964	0.487685

Table 3

Results of calculation of sample functions

Low-temperature mode				High-temperature mode			
SiO_2		CaO		SiO_2		CaO	
$M(X_i)$	$S^2(X_i)$	$M(X_i)$	$S^2(X_i)$	$M(X_i)$	$S^2(X_i)$	$M(X_i)$	$S^2(X_i)$
–0.5896	0.08367	–0.5527	0.20333	0.5451	0.15824	0.3261	0.17882

From the general form of equation (2) it follows that its left part is a linear function, and the right part is a numerical threshold value of the discriminant function, separating two classes – Low-temperature mode and High-temperature mode. That is, the assessment of the melting temperature mode is performed based on the conditions:

$$a_1x_1 + a_2x_2 \geq f_0 \rightarrow \text{High-temperature mode,}$$

$$a_1x_1 + a_2x_2 < f_0 \rightarrow \text{Low-temperature mode.} \quad (8)$$

By calculating the parameters of the discriminant function, the coefficients a_1, a_2 and f_0 according to formulas (2)–(6) based on the data in **Table 2**, a rule was obtained that allows one to determine whether the Low-temperature mode or High-temperature melting mode was used:

$$10.279x_1 + 22.061x_2 \geq 1.086 \rightarrow \text{High-temperature mode,}$$

$$10.279x_1 + 22.061x_2 < 1.086 \rightarrow \text{Low-temperature mode.} \quad (9)$$

Fig. 1 shows the points lying on the theoretical curve of the distribution density of the discriminant function value (the left part of rule (9)) for both classes and the threshold value of the function (the right part of rule (9)).

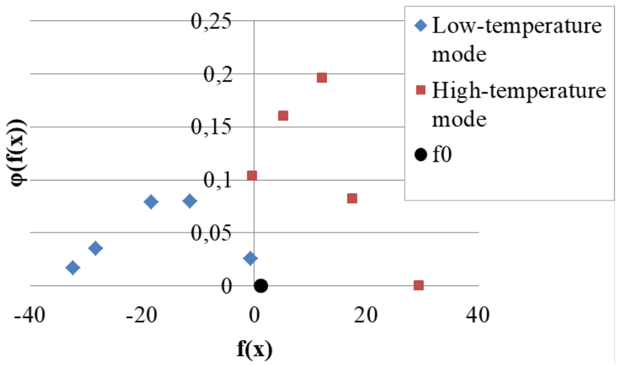

Fig. 1. Probability densities $p_1(f)$, $p_2(f)$ for Low-temperature mode and High-temperature mode

Visualization of class separation based on the obtained rule (9) is presented in **Fig. 2**.

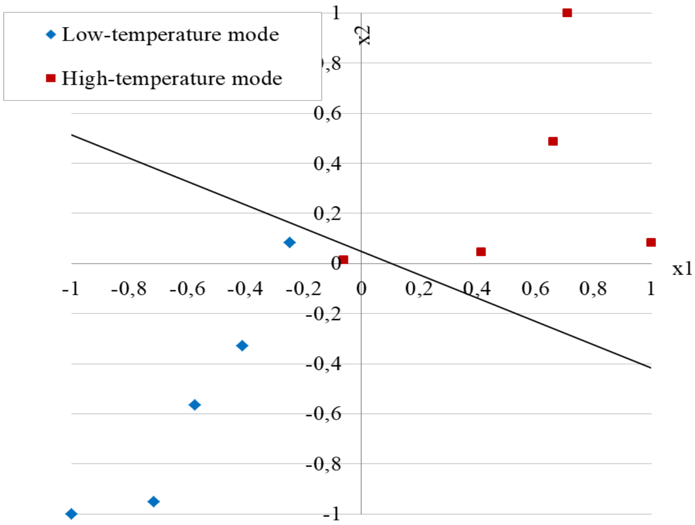

Fig. 2. Class division based on rule (9)

Rule (9) is written in standardized values. In its natural form it is presented as follows:

$$10.279\frac{(SiO_2)-57.75}{18.43} + 22.061\frac{(CaO)-3.095}{1.015} \geq 1.086 \rightarrow \text{High-temperature mode,}$$

$$10.279\frac{(\mathrm{SiO_2})-57.75}{18.43}+22.061\frac{(\mathrm{CaO})-3.095}{1.015}<1.086 \rightarrow \text{Low-temperature mode.} \qquad (10)$$

The rule in the form of (10) allows, based on the slag analysis data for the content of SiO_2 and CaO, to determine whether the melting process was carried out in Low-temperature mode or High-temperature mode. To do this, it is sufficient to substitute the actual values of the SiO_2 and CaO content into (10).

4. Discussion

As can be seen from **Fig. 2**, out of ten points only one was erroneously assigned to another class – Low-temperature mode instead of High-temperature mode. This allows to speak about high resolution of the obtained rule – classification accuracy was 90 %. Therefore, rule (9) in normalized form or (10) in its natural form can be effectively used to assess the melting temperature mode, despite its simplicity. In practical application, this allows to assess whether the melting process took place in the temperature range T=1200–1300 °C or T=1400–1500 °C. In addition, it is possible to say that if the melting was carried out in the low-temperature mode, then the confidence interval of the content of slag components SiO_2 and CaO, the boundaries of which are determined by the value $\pm\frac{ts}{\sqrt{N}}$, is 46.88±6.62 % and 2.53±1.27 %, respectively. If the melting was carried out in a high-temperature mode, the confidence interval is 67.8±9.1 % for SiO_2 and 3.43±0.53 % for CaO. That is, with a probability of P=0.95, when melting at a temperature of 1200–1300 °C, the content of components in the slag will be (SiO_2)=(40.26–53.5) %, (CaO)=(1.26–3.8) %. When melting at a temperature of 1400–1500 °C, the content of components in the slag will be (SiO_2)=(58.7–76.9) %, (CaO)=(2.9–3.96) %.

The use of rule (10) also allows to assess the risks of chemical wear of the lining. Thus, if the first of the conditions (10) is met, the risk of reaction (I) and the formation of low-melting complex compounds, including iron, silicon and manganese oxides, increases.

The results obtained in the form of the diagnostic rule (10) are limited by the range of variation of the factor values. Therefore, in practical application, it is necessary to check whether the slag content for the SiO_2 and CaO components in a particular melt corresponds to this range. It is also important to check whether the distribution law of the slag content for the SiO_2 and CaO components corresponds to the normal one. This condition may not always be met, so it may be necessary to pre-filter the data if the data sample is large. Of course, this is a problem in real production conditions. It is also important to point out the drawback of the study – the rule is based on a small sample of data that was available. This means that increasing the accuracy of the diagnostic rule may be possible by expanding the data sample, which can be the subject of further development of the study.

5. Conclusions

A diagnostic rule has been obtained that allows estimating the temperature conditions of induction melting based on available data on the SiO_2 and CaO content in the slag. This rule has a simple structure and allows obtaining a fairly accurate forecast – 90 %.

It has been established that when melting at a temperature of 1200–1300 °C, the content of components in the slag will be (SiO_2)=(40.26–53.5) %, (CaO)=(1.26–3.8) %. When melting at a temperature of 1400-1500 °C, the content of components in the slag will be (SiO_2)=(58.7–76.9) %, (CaO)=(2.9–3.96) %. The obtained rule allows to assess the risk of chemical wear of the lining due to the development of a reaction between the carbon of the melt and the silica of the lining and the formation of low-melting compounds that continuously interact with the lining during the passage of the melt front.

Conflict of interest

The authors declare that there is no conflict of interest in relation to this paper, as well as the published research results, including the financial aspects of conducting the research, obtaining and using its results, as well as any non-financial personal relationships.

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Data availability

Data will be made available on reasonable request.

Use of artificial intelligence

The authors confirm that they did not use artificial intelligence technologies when creating the current work.

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